Long-term Impact Assessment of Disasters through Predictive Analytics

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Abstract
Disaster is a significant problem that extensively affects society and the community. Predicting the effects of a disaster is difficult for several reasons. The primary aim of this study is to evaluate the effects of disasters across several timeframes, ranging from immediate to long-term. To construct a plausible model, the proposed solution considers the available disaster datasets from various agencies (e.g. SMS, ISC, NDMC etc.).

A methodology for assessing the long-term effects of disasters utilizing well-liked machine learning techniques is presented here. It consists of the algorithms for Decision Tree, Random Forest, Gradient Boost Decision Tree and XG Boost. The algorithms' classification accuracy for the provided data sets is 56%, 63%, 83% and 91% respectively. The proposed work also examines the various levels of disaster severity and suggests solutions for each level to improve preparedness and response measures.

Keywords: Classification, Data analytics, Emergency management, Recommendations, Severity level, XG boost.

Introduction

Every year, many people around the globe are affected by natural and man-made disasters. People often lose their lives because of these things. Disasters not only kill people but often cause significant damage to property and infrastructure[23]. Before, during and after a tragedy, disaster management tasks are carried out to keep people and property safe, limit the damage to the economy and get things back to normal[16]. Due to the complexity of disasters and the importance and difficulty of disaster operations, strong decisions need to be made with the help of technology, especially artificial intelligence (AI). Recent progress in machine learning and deep learning algorithms has made this possible[13].

India is a country that is very likely to be hit by disasters and a lot of its land is in high-risk areas. More than 44 million people in India are thought to be touched by natural disasters every year. More than 70% of the people live in 80% of the land that is subject to cyclones, floods, landslides, drought, earthquakes and other localized disasters[2]. The disaster management cycle is an ongoing process that includes various stages of planning and getting ready for disasters. These stages include long-term mitigation (also called "mitigation/prevention"), short-term preparation and prevention (also called "preparedness"), reducing the effects of a disaster through response and rescue efforts (i.e. "response") and restoration through clean-up and reconstruction (i.e. "recovery").

However, the disaster risk management cycle as mentioned in figure 1 is divided into two distinct phases: i) pre-disaster which includes preparedness and mitigation for disasters and ii) post-disaster which includes disaster response[17]. Disasters including hurricanes, earthquakes, floods, wildfires and landslides are examples. Due to the misuse of technological advancements, there are man-made disasters like terrorism, war, biological/chemical threats, cyber-attacks etc.[21]

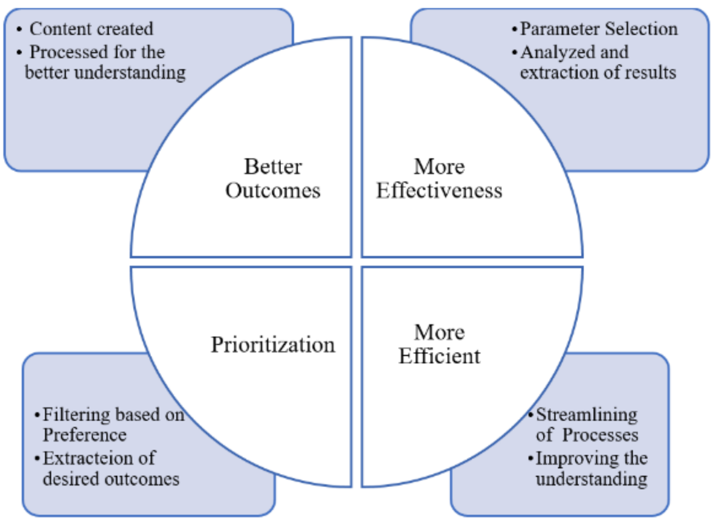

Figure 1: Disaster management cycle

Natural disasters and technical disasters are the two primary categories into which catastrophes can be divided, according to the Emergency Events Database (EM-DAT) terminology[18]. A few Machine Learning and Deep Learning techniques are employed in the AI tools that support catastrophe management in all stages. Support vector machines (SVM), Naïve Bayes (NB) techniques, decision trees (DT), random forests (RF), logistic regression (LR), Gradient Boost Decision Tree (GBDT), Extreme Gradient Boost (XG Boost) and K-nearest neighbor (KNN) clustering algorithm are examples of machine learning (ML) techniques.

Disasters have long-term repercussions on society, the environment and human existence. The effects of disasters in the future can be predicted using historical data sets. A range of data formats are present in datasets. Video, audio, text, social data and photographs are few examples. These kinds of data can be analyzed with the help of contemporary machine learning methods. The accuracy of forecasts is dependent upon the process in which the appropriate data sets are processed. Predictive analytics presents a chance to address post-disaster issues that exist now. Authorities can make the right decisions with the use of analytical tools. Analyzing and accurately forecasting the effects of disasters on people, property, animals, the economy, the environment and other factors are very challenging.

Because of the constantly changing environment, it is challenging to forecast the effects of natural disasters[12]. To analyze information effectively and visualize it to make critical decisions, historical data is essential. Information about related disasters is used to create models that forecast future effects. This will support Governments and authorities in taking preventative action and creating a plan for the years after the disaster. The outcomes also forecast the effects of calamities in the upcoming years. The necessary datasets can be obtained from organizations that are active in the field. Websites that offer datasets such as data.gov, Kaggle, GSI, NDMC, NOAA and Datahub, can be used for developing the model.

The judiciary and Government agencies have also supplied several confirmed data that offer an evaluation of big catastrophes according to factors including the number of fatalities, the amount of economic damage and the impacted area. Under the Disaster Management Strategy Act, the policy is also being applied nationally[3]. They are escaping the current calamity and preparing for what is ahead. Nevertheless, it is difficult to forecast which regions will be more severely impacted by a disaster and to depict the effects of a disaster that will occur soon. The predictive analysis-based approach that has been suggested can be applied to the identification, assessment, mitigation and reconstruction of hazards[1].

Material and Methods

The proposed methodology can be used to develop strategies and provide suggestions to improve disaster management. The proposed methodology examines the datasets related to disasters that have been sourced from various agencies[14]. Examples include SMS, ISC, NDMC and publicly available datasets. To create a workable model, it is necessary to provide authentic datasets on natural and man-made disasters. Historical datasets include information about people who were affected by a tragedy, the contributions of an organization and other factors that were affected.

For the purposes of predictive analysis, a model is developed in the second phase of the approach. In this method, more necessary data is recovered from the extracted raw data by applying pruning and filtering procedures. Pruning reduces the size of the decision tree by removing branches that are not directly contributing to the classification of instances. Conversely, a data filtering function is to choose a portion of a data collection for examination. The next step is an examination carried out by data analysis tools and algorithms to determine the quality of the trained model.

Decision tree and Random Forest are the most widely used models in these categories[11,22]. Besides the conventional methods, there are also other sophisticated machine learning models available such as gradient boost decision tree methodology and the XG Boost ML approach. The suggested method's process flow architecture is depicted in the accompanying figure 2.

Understanding the patterns, trends and risk factors connected to catastrophes requires analyzing data from disaster datasets. There are multiple steps in the process, from preparing the data to interpreting the findings. The collection of disaster data for the purpose of prediction or analysis is an essential and pivotal stage in comprehending, mitigating and responding to disasters in an efficient manner.

Table 1
Disaster type and its affected parameters

Selection of Disaster	Affected Parameters	Impacts based on Prediction
Drought, Earthquake, Volcanic, Floods	People Death	Based on the available datasets, predictions for the possible effects can be calculated.
	People Injured	
	People Affected	
	People Left Homeless	
	Reconstruction Cost	
	Insured Damages	

The procedure entails the collection of pertinent data from several sources such as Governmental entities, international organizations, academic institutions and public records[10].

Different parameters might be used to provide suggestions for the future based on the influence of the event that happened[4]. Depending on the nature, severity and location of the disaster, these effects can vary. Table 1 displays the proposed disaster categories and their affected attributes for the purpose of impact assessment.

The gathered disaster data sets from many agencies are displayed in the figures 3 and figure 4 along with the sequential processing for implementation and prediction. Several procedures are involved in disaster data analysis to collect insightful information from disaster-related datasets. By taking these actions, decision-makers, emergency responders and researchers can better comprehend the nature of catastrophes, evaluate risk and establish plans for response and mitigation[8,26].

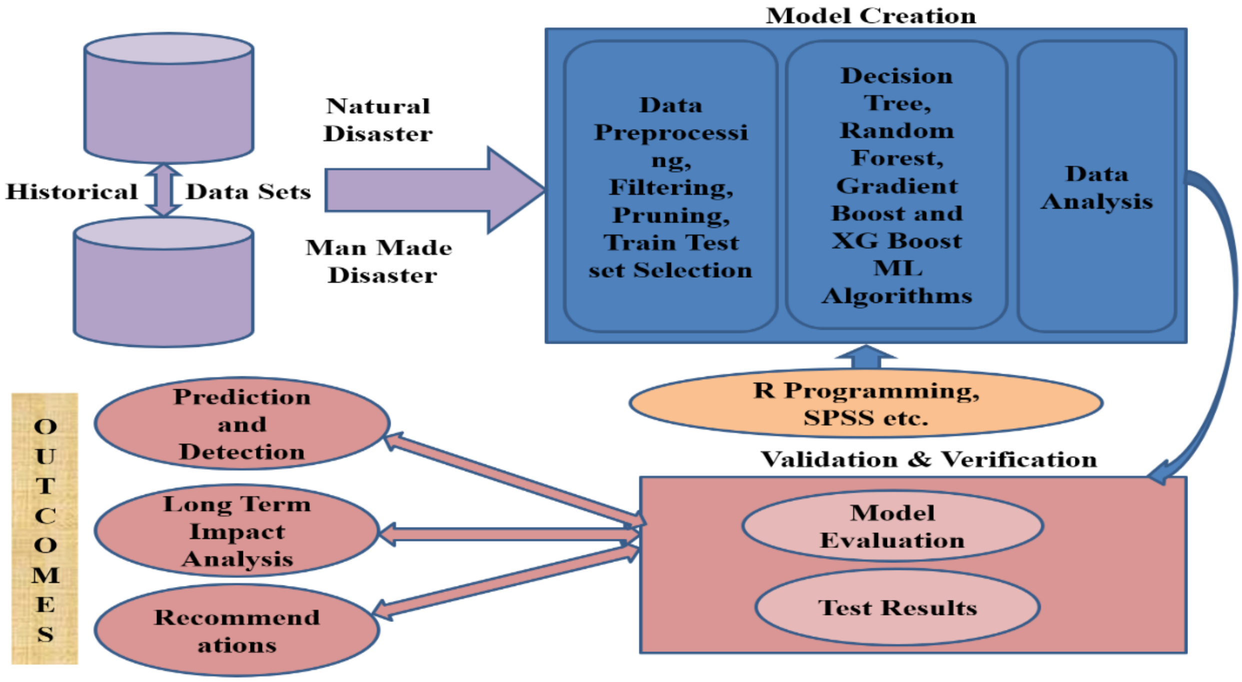

Figure 2: Process flow architecture

Year	Number of deaths from drought	Number of people injured from drought	Number of people affected from drought	Number of people left homeless from drought	Reconstruction costs from drought	Insured damages against drought	Number of deaths from earthquakes	Number of people injured from earthquakes	Number of people affected by earthquakes	Number of people left homeless from earthquakes	Reconstruction costs from earthquakes	Insured damages against earthquakes	Number of deaths from floods	Number of people injured from floods	Number of people affected by floods	Number of people left homeless from floods	Reconstruction costs from floods	Insured damages against floods	Number of deaths from storms	Number of people injured from storms	Number of people affected by storms	Number of people left homeless from storms	Reconstruction costs from storms	Insured damages against storms
1900	0	0	0	0	0	0	215.1	200	0	0	0	0	5.1	0	0	0	0	0	0	0	0	0	0	0
1905	0	0	4800	0	0	0	10.7	0	4800	0	0	0	10.7	0	0	0	0	0	0	0	0	0	0	0
1907	0	0	0	0	0	0	48.2	15.5	68404.4	750	0	0	32.1	14	59404.4	750	0	0	0	0	0	0	0	0
1916	0	0	0	0	0	0	58.3	351.8	25344	658	0	0	0	0	19100	0	0	0	0	0	0	0	0	0
1920	0	0	0	0	0	0	1038.9	394.7	43624	9578.5	0	20	199	30	16435.5	1765	0	20	1	0	0	0	0	0
1920	3.7	0	476000	0	0	0	448.7	197.2	567969.4	3909.5	0	0	117.5	26.7	13537.5	2340	0	0	33.1	0	2265.6	0	0	0
1924	0	0	1525000	0	0	0	263.1	5918.4	1567389.9	7790.5	0	0	137	60.7	38113.9	3422	0	0	15.1	1.5	904.5	0	0	0
1924	1100	0	0	0	0	0	1111.7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1925	8500	0	3200	0	0	0	8501.2	0	3200	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1926	2400	0	0	0	0	0	2701.2	0	0	0	0	0	300	0	0	0	0	0	0	0	0	0	0	0
1926	0	0	0	0	0	0	2.2	13	0	750	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1927	5000	0	0	0	0	0	5044.1	0	0	0	0	0	0	0	0	0	0	0	16.5	0	0	0	0	0
1927	0	0	0	0	0	0	216.2	502.8	0	12925	0	0	23.7	0	0	0	0	0	64.2	0	0	0	0	0
1928	205	0	963348.3	0	0	0	1643	2736.9	1064906.5	6204.1	0	0	134.3	25.9	84298.2	2580	0	0	15.2	7.9	12500	1650	0	0
1935	11900	0	1951200	0	0	0	12095.7	171.8	2806919	31248.2	0	0	132.8	90.3	440799.1	19063.2	0	0	41.5	61.5	412419.9	4885	0	0
1935	55495.4	0	8256606.7	0	0	0	56252.9	1270.5	9068311.2	238514.3	0	30100	165	46.9	558345.6	176312.7	0	30100	108	164.6	199564.8	12510	0	0
1936	23.9	0	8618424.6	0	0	0	991.8	3402.7	10308199.2	299935.3	1400	11780	731.7	1928.3	1219772	214126.5	0	0	113	408.7	356419	80563.9	1400	11780
1942	88.8	0	11948903.3	0	0	0	1422.9	2471.7	14556934.3	250118.5	13363.2	6950	794.8	377.8	2187219	145591.4	13363.2	5150	127.3	673.1	377065.3	67732.5	0	0
1942	2000	0	12552199.8	0	0	0	3283.3	2118.8	16760448.6	102625.6	39310	83100	724.5	927.6	3142339	75926.1	39310	14700	291.6	1053.1	752233.5	23717.1	0	48400
1943	0	0	0	0	0	0	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1943	0	0	0	0	0	0	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1944	0	0	0	0	0	0	15	10.8	294	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1945	0	0	0	0	0	0	4.3	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1948	0	0	0	0	0	0	2.6	28.8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1949	0	0	0	0	0	0	3.5	35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1950	0	0	320000	0	0	0	12.6	3.1	320643.5	634	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1950	0	0	0	0	0	0	1.5	0	4860	0	0	0	1.5	0	4650	0	0	0	0	0	0	0	0	0
1950	0	0	0	0	0	0	1.5	0	60163.4	22.5	0	0	0.4	0	7648.4	0	0	0	0.8	0	52500	0	0	0
1950	0	0	0	0	0	0	6.6	102.7	51940	0	0	0	0.4	0.2	8260	0	0	0	0	0	0	0	0	0
1952	0	0	0	0	0	0	1.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 3: All major disaster raw datasets collected from various sources

https://doi.org/10.25303/173da08015

	Number of deaths from drought	Number of people injured from drought	Number of people affected from drought	Number of people left homeless from drought	Reconstruction costs from drought	Insured damages against drought	Number of deaths from earthquakes	Number of people injured from earthquakes	Number of people affected by earthquakes	Number of people left homeless from earthquakes	...	Number of people affected by extreme temperatures	Number of people left homeless from extreme temperatures	R
0	0.0	0.0	0.0	0	0.0	0.0	210.0	200.0	0.0	0.0	...	0.0	0.0	
1	0.0	0.0	4800.0	0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	
2	0.0	0.0	0.0	0	0.0	0.0	6.1	1.5	9000.0	0.0	...	0.0	0.0	
3	0.0	0.0	0.0	0	0.0	0.0	51.3	351.8	6244.0	658.0	...	0.0	0.0	
4	0.0	0.0	0.0	0	0.0	0.0	742.6	358.3	27168.5	7702.5	...	20.0	0.0	

Figure 4: Pre-processed data with selected disaster datasets along with all possible attributes

```
                                        precision    recall  f1-score   support

                                   1       0.61      0.95      0.74       918
Confusion matrix                   2       0.00      0.00      0.00       123
                                   3       0.32      0.30      0.31       234
 [[876   0  34   8   0]            4       0.25      0.07      0.11       216
 [ 30   0  77  16   0]             5       0.75      0.01      0.03       235
 [142   0  71  21   0]
 [176   0  23  16   1]      accuracy                           0.56      1726
 [215   0  15   2   3]]     macro avg       0.39      0.27      0.24      1726
                          weighted avg       0.50      0.56      0.46      1726
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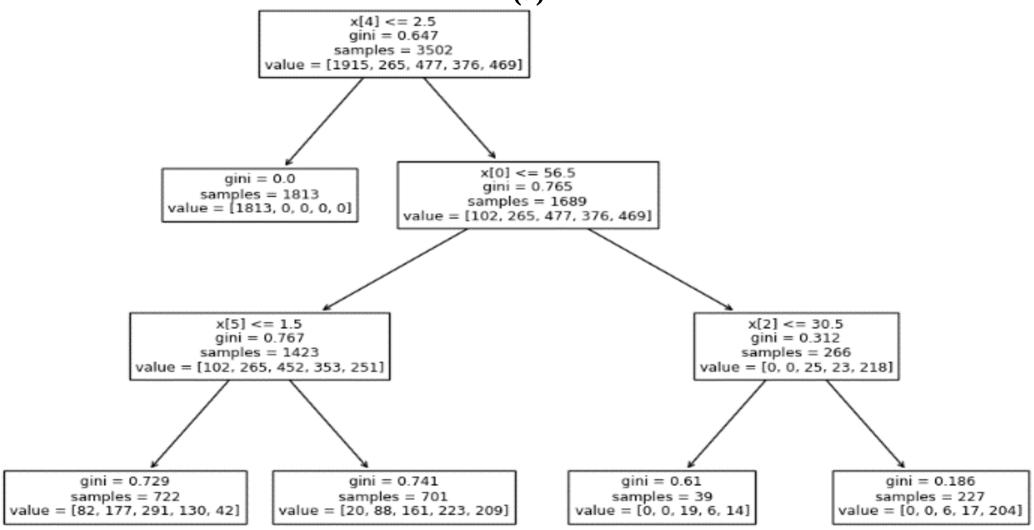
(a)



(b)

Figure 5: Classification evaluation of disaster datasets using decision tree (a) confusion matrix and classification report (b) classification tree

Results and Discussion

Relevant findings focus on the identification and forecasting of both man-made and natural disasters, the direct and indirect assessment of long-term impacts and policymakers' recommendations. It also aids in the management of the effects of disasters and the creation of improved planning techniques to lessen their effects. The foundation for long-term disaster prediction is made up of datasets from various authorities as well as adaptability to novel dangerous scenarios. The raw disaster data is gathered from multiple sources for pre-processing, analysis and prediction.

During the cleansing process, superfluous record branches are eliminated. Clean-up techniques eliminate redundant data that is unrelated to a particular calamity. Data analysis tools are used to further divide the dataset for training and testing once the data has been collected and preprocessed. Further, sophisticated machine learning methods are used to classify the dataset. The purpose of model evaluation is to verify the trained model’s accuracy.

Decision Tree: A popular machine learning approach for a variety of applications including the examination of disaster information, is decision trees[7]. Classification difficulties such as determining whether an occurrence is a disaster or not based on several aspects or attributes, are handy with decision tree. Decision trees can handle both binary classification problems (e.g. disaster or not) as well as multi-class classification problems (e.g. categorizing multiple sorts of disasters). However, depending on the quantity and quality of data as well as the selection of hyperparameters, their performance may differ. Therefore, to get the best outcomes for a particular disaster prediction assignment, it is critical to experiment, iterate and refine the model[19]. Figure 5 illustrates how disaster data is examined using the decision tree.

Random Forest: The Random Forest algorithm is a robust machine learning technique that has considerable efficacy when applied to disaster datasets. It may be efficiently employed for a range of tasks including classification, regression and feature selection[5]. The Random Forest algorithm is especially advantageous in the context of intricate and high-dimensional datasets. It is a flexible and reliable method that works well for disaster datasets because it can handle noisy, high-dimensional data and can find complex patterns based on the provided features. Random forest can help in making disaster prediction, risk assessment and decision support tools better when used correctly[25]. Figure 6 illustrates how disaster data is examined using a random forest machine learning algorithm.

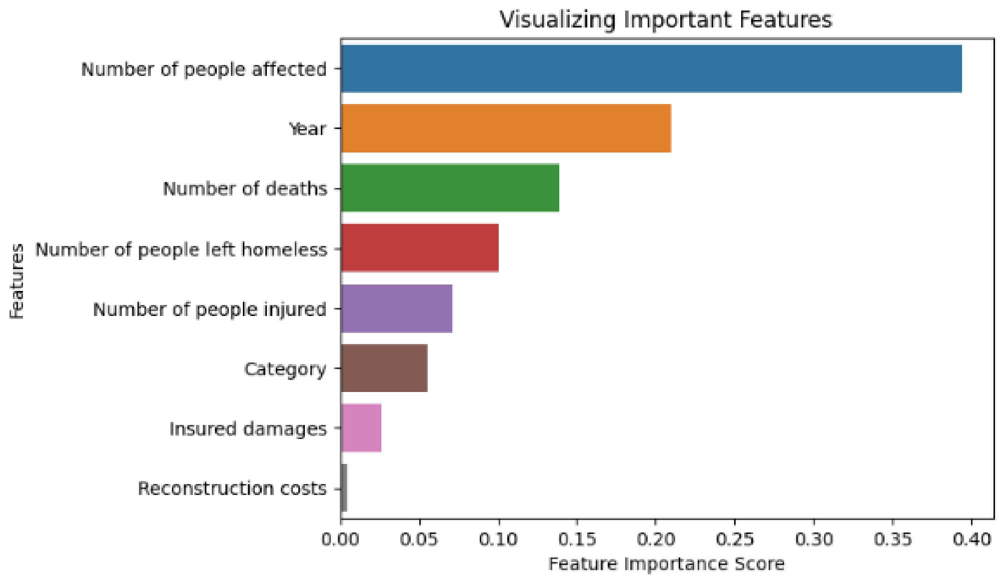
Gradient Boost Decision Tree: Gradient boost decision tree is an effective machine learning approach that is widely utilized for tasks like regression and classification in disaster datasets as well as other fields. It is renowned for its capacity to combine the predictions of several weak learners (often decision trees) in an ensemble to create extremely accurate predictive models[24]. Because gradient boosting can handle complex relationships in data, adjust to different levels of feature relevance and produce excellent predictive accuracy, it is a preferred choice for disaster prediction jobs. Gradient Boosting, when used properly, can make a big difference in disaster risk assessment and response strategy[9]. Figure 7 illustrates how disaster data is examined using a gradient boost decision tree machine learning algorithm.

```
Confusion matrix

 [[905   8   3   1   1]
 [ 39  63  17   4   0]
 [143   5  75   9   2]
 [177   0   7  30   2]
 [215   0   7   4   9]]
```

	precision	recall	f1-score	support
1	0.61	0.99	0.76	918
2	0.83	0.51	0.63	123
3	0.69	0.32	0.44	234
4	0.62	0.14	0.23	216
5	0.64	0.04	0.07	235
accuracy			0.63	1726
macro avg	0.68	0.40	0.43	1726
weighted avg	0.64	0.63	0.54	1726

(a)



(b)

Figure 6: Classification evaluation of disaster datasets using Random Forest (a) confusion matrix and classification report (b) feature extraction

Extreme Gradient Boosting: Extreme Gradient Boosting (XGBoost) is a cutting-edge machine learning algorithm that has become famous because it works so well at many things such as analyzing disaster datasets. XGBoost is an extension of gradient boosting that has a more regularized model structure and a very fast implementation[6]. This makes it perfect for datasets that are huge and complicated. XGBoost is well known for its capacity to manage huge datasets, intricate data linkages and high prediction accuracy. It has been effectively used in several fields such as risk assessment and disaster prediction where the accuracy of forecasts can have a big influence on preparations for disaster management and response[15,20].

Figure 8 illustrates how disaster data is examined using extreme gradient boost machine learning algorithm. The disaster severity levels, level names, level descriptions and suggestions based on the level are displayed in table 2.

Table 2
Disaster severity levels and recommendations

Severity Levels	Level Name	Description	Recommendations
1	Low	Low-severity events rarely cause significant damage to people or property. Small-scale localized floods, small wildfires and limited power outages are some examples.	Community Education: It is important to teach communities about fundamental preparedness steps including assembling emergency kits and making evacuation plans. Mitigation Attempts: Preventive measures that are put into place, such as buildings that are flood-resistant and have firebreaks, can lessen the effects of low-severity disasters.
2	Minor	Minor impacts can encompass several events such as localized flooding, power outages, small-scale wildfires and minor earthquakes. Although the consequences of these events may not be of a catastrophic nature, it is imperative to implement efficient measures to mitigate their effects and guarantee the protection and welfare of those impacted regions.	Create Emergency Kits: Encourage people to put together basic emergency kits for themselves and their families. People can survive with these kits during small disturbances. Resource Stockpiling: During minor disasters, local authorities should keep a stock of necessary supplies on hand, such as portable generators, emergency lighting and sandbags, so that they can be rapidly dispatched to impacted areas.
3	Moderate	Larger areas and populations may be impacted by disasters of moderate severity, which also poses a considerable risk to human life and some infrastructure damage. Regional earthquakes, mild floods and extensive power outages are a few examples.	Emergency Response Plans: Communities need to have clear emergency response plans that cover things like communication tactics, shelter locations and evacuation protocols. Resource Stockpiling: To support impacted communities in the early wake of a disaster, local authorities should stockpile necessities like food, water and medical supplies.
4	Major	Disasters of major magnitude have a profound impact on human lives, infrastructure and the environment. Major examples include earthquakes, cyclones and tsunamis.	Early Warning Systems: By putting advanced warning systems in place ahead of time, people can be evacuated and vital infrastructure can be secured. Mutual Aid Agreements: To guarantee the availability of extra personnel and resources during a high-severity crisis, establish mutual aid agreements with nearby nations or regions.
5	Extreme	Extreme-severity disasters are characterized by their catastrophic nature, possessing the potential to surpass the capacity of even the most well-equipped and resilient populations. Super volcanic eruptions, large-scale nuclear accidents and world pandemics are some examples.	International Collaboration: Make sure that response efforts are coordinated around the world by working with governments and international groups to pool resources and knowledge. Risk reduction: Spend money on study and technology to learn how to predict and lessen the effects of disasters of the worst kind.

Confusion Matrix:

572	6	4	2	1
4	27	18	15	2
1	14	101	16	24
2	9	16	73	18
0	3	9	14	100

	precision	recall	f1-score	support
1	0.99	0.98	0.98	585
2	0.46	0.41	0.43	66
3	0.68	0.65	0.66	156
4	0.61	0.62	0.61	118
5	0.69	0.79	0.74	126
accuracy			0.83	1051
macro avg	0.69	0.69	0.69	1051
weighted avg	0.83	0.83	0.83	1051

Figure 7: Classification evaluation of disaster datasets using Gradient Boost Decision Tree

Confusion Matrix:

574	10	1	0	0
0	50	15	1	0
0	6	127	20	3
0	0	10	104	4
0	0	4	23	99

Classification Report

	precision	recall	f1-score	support
0	1.00	0.98	0.99	585
1	0.76	0.76	0.76	66
2	0.81	0.81	0.81	156
3	0.70	0.88	0.78	118
4	0.93	0.79	0.85	126
accuracy			0.91	1051
macro avg	0.84	0.84	0.84	1051
weighted avg	0.92	0.91	0.91	1051

Figure 8: Classification evaluation of disaster datasets using XG Boost

Conclusion

The nature and timing of a disaster will determine how it affects people today and tomorrow. But because they are more obvious than long-term consequences, direct effects get greater attention than indirect effects. This kind of impact documentation is not very explicit. Understanding the varied nature and scale of these repercussions is something that Governments and pertinent bodies need to consider. Predictive analytics is a set of methodologies for assessing the long-term effects of disasters that employ statistical and other empirical techniques to estimate future events based on past events.

It has been demonstrated that data analysis approaches may accurately and quickly forecast the optimal outcomes. This procedure involves the examination of past data. Based on evaluation using the most recent machine learning algorithms, we can forecast and suggest future occurrences. The model has proposed recommendations depending on the severity levels.

Acknowledgement

Our heartfelt thanks go to Scientist Er. C. M. Bhatt, Disaster Management Studies Department Course Director, RS and GIS PG Course, CSSTEAP (UN Affiliated) Indian Institute of Remote Sensing, ISRO, Dept. of Space, Govt. of India for valuable guidance for data collection.

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(Received 18th October 2023, accepted 16th December 2023)